



Further Analysis of Stability for Lambert's Method Based on Euler's Rule

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Abstract—Lambert [1] proposed a one-step method based on Euler's rule which effectively copes with ordinary differential equations. In the paper, he proved its stability for the equation of the type $y' = Ay$, where A is a real symmetric matrix. We extend the concept and prove the stability when A is a real normal matrix.

Keywords—Stability analysis, Lambert's method, Nonlinear method, Numerical ODEs, Real normal matrix.

1. INTRODUCTION

We consider the initial value problem

$$y' = f(x, y), \quad y(a) = y_0, \quad (1)$$

where $y, f \in R^m$ and $x \in [a, b]$. Lambert [1] has proposed a one-step method with self-adjusted steplength which is based on Euler's rule. It is given by

$$y_{n+1} = y_n + h_n f_n, \quad \text{with } h_n = \min(h_0, h_n^*), \quad h_n^* = \frac{f_n^\top f_n}{|f_n^\top A f_n|}, \quad (2)$$

where h_0 is the initial steplength and $\frac{\partial f}{\partial y}|_n$ is used instead of A when equation (1) is nonlinear. The advantage of this method is that we can obtain a cheap low-accuracy solution to a stiff system of ordinary differential equations.

In fact, in his paper [1], Lambert proved the following theorem.

THEOREM 1. *Let the method (2) be applied to the linear problem*

$$y' = Ay, \quad y(x_0) = y_0,$$

where A is a real symmetric $m \times m$ matrix with eigenvalues λ_t , $t = 1, 2, \dots, m$, satisfying

$$\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_m < 0.$$

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Then as $n \rightarrow \infty$, $y_n \rightarrow 0$ monotonically in the L_2 -norm.

A lemma below, which was also proved in [1], supports the proof of Theorem 1.

LEMMA 1. Let B be a real symmetric $m \times m$ matrix with eigenvalues α_t , $t = 1, 2, \dots, m$, satisfying

$$\alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_m < 0.$$

Then for any $w \in R^m$, $w \neq 0$, there hold

$$\alpha_1 \leq \frac{w^\top B w}{w^\top w} \leq \alpha_m, \quad \frac{(w^\top w)^2}{(w^\top B w)(w^\top B^{-1} w)} \leq 1.$$

Thus the statement of Theorem 1 is only valid for the linear system with real symmetric matrix coefficients. This means Lambert's method can give a stable and cheap approximation for the exponentially decreasing solutions without oscillation. But our preliminary numerical observations suggest a possibility to extend the stability property of the method over the real symmetric case.

Our aim here is to extend Theorem 1 when A is a real normal matrix. In Section 4, we will show that some numerical experiments confirm our theorem.

2. A KEY LEMMA

Throughout Sections 2 and 3, we use the following assumption on matrices.

ASSUMPTION A. A real normal $m \times m$ matrix has its eigenvalues λ_i for $i = 1, 2, \dots, m$ such that

$$\begin{aligned} \lambda_{2i-1} &= \alpha_i + \sqrt{-1} \cdot \beta_i, & \lambda_{2i} &= \bar{\lambda}_{2i-1}, & \text{for } 1 \leq i \leq k, \\ \lambda_i &\in R, & & & \text{for } 2k+1 \leq i \leq m, \end{aligned}$$

and $\Re \lambda_i < 0$ for $1 \leq i \leq m$.

LEMMA 2. Assume that a matrix B satisfies Assumption A. Let $l = \min \Re \lambda_i$ and $L = \max \Re \lambda_i$; then for any $w = [w_1, w_2, \dots, w_m]^\top \in R^m$ and $w \neq 0$, the following inequality holds:

$$l \leq \frac{w^\top B w}{w^\top w} = \frac{(1/2)w^\top (B^\top + B) w}{w^\top w} \leq L. \quad (3)$$

Furthermore, the inequality

$$\frac{(w^\top w)^2}{(w^\top B w) \cdot (1/2)w^\top (B^{-1} + B^{-\top}) w} \leq 2 - \delta \quad (4)$$

holds with a certain positive δ for any $w \in R^m$ if and only if the inequality $|\beta_i/\alpha_i| < 1$ holds for all i ($1 \leq i \leq k$).

PROOF. Since the matrix B is real and normal, there exists [2, p. 105] a real orthogonal matrix Q such that

$$Q^\top B Q = \Lambda = \begin{bmatrix} \Lambda_1 & & & 0 \\ & \Lambda_2 & & \\ & & \ddots & \\ 0 & & & \Lambda_k \\ & & & & \tilde{\Lambda} \end{bmatrix},$$

where the submatrices are given by

$$\Lambda_i = \begin{bmatrix} \alpha_i & \beta_i \\ -\beta_i & \alpha_i \end{bmatrix}, \quad \tilde{\Lambda} = \begin{bmatrix} \lambda_{2k+1} & & 0 \\ & \ddots & \\ 0 & & \lambda_m \end{bmatrix}.$$

Let

$$\mathbf{w} = \mathbf{Q}\mathbf{u}, \quad \mathbf{u} = [u_1, u_2, \dots, u_m]^\top$$

and $v_i = u_{2i-1}^2 + u_{2i}^2$ for $1 \leq i \leq k$; then we have the following identities:

$$\mathbf{w}^\top \mathbf{B} \mathbf{w} = \mathbf{u}^\top \mathbf{\Lambda} \mathbf{u} = \sum_{i=1}^k \alpha_i v_i + \sum_{i=2k+1}^m \lambda_i u_i^2, \quad (5)$$

$$\begin{aligned} \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^\top + \mathbf{B}) \mathbf{w} &= \frac{1}{2} \mathbf{u}^\top (\mathbf{Q}^\top \mathbf{B}^\top \mathbf{Q} + \mathbf{Q}^\top \mathbf{B} \mathbf{Q}) \mathbf{u} \\ &= \frac{1}{2} \mathbf{u}^\top (\mathbf{\Lambda}^\top + \mathbf{\Lambda}) \mathbf{u} \\ &= \sum_{i=1}^k \alpha_i v_i + \sum_{i=2k+1}^m \lambda_i u_i^2 = \mathbf{w}^\top \mathbf{B} \mathbf{w}, \end{aligned} \quad (6)$$

$$\begin{aligned} \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} &= \frac{1}{2} \mathbf{u}^\top (\mathbf{Q}^\top \mathbf{B}^{-1} \mathbf{Q} + \mathbf{Q}^\top \mathbf{B}^{-\top} \mathbf{Q}) \mathbf{u} \\ &= \frac{1}{2} \mathbf{u}^\top (\mathbf{\Lambda}^{-1} + \mathbf{\Lambda}^{-\top}) \mathbf{u} \\ &= \frac{1}{2} \left[\sum_{i=1}^k \frac{2(1/\alpha_i)}{1 + (\beta_i/\alpha_i)^2} v_i + \sum_{i=2k+1}^m \frac{2}{\lambda_i} u_i^2 \right], \end{aligned} \quad (7)$$

$$\mathbf{w}^\top \mathbf{w} = \mathbf{u}^\top \mathbf{u} = \sum_{i=1}^m u_i^2. \quad (8)$$

Let $\sigma_{2i-1} = \sigma_{2i} = \alpha_i$ for $1 \leq i \leq k$ and $\sigma_i = \lambda_i$ for $2k+1 \leq i \leq m$. Equations (5) and (8) yield

$$\frac{\mathbf{w}^\top \mathbf{B} \mathbf{w}}{\mathbf{w}^\top \mathbf{w}} = \frac{\sum_{i=1}^k \alpha_i v_i + \sum_{i=2k+1}^m \lambda_i u_i^2}{\sum_{i=1}^m u_i^2} = \frac{\sum_{i=1}^m \sigma_i u_i^2}{\sum_{i=1}^m u_i^2},$$

and the desired result (3) follows from (6) and the fact that

$$l \sum_{i=1}^m u_i^2 \leq \sum_{i=1}^m \sigma_i u_i^2 \leq L \sum_{i=1}^m u_i^2.$$

Using (5), (7), and (8), we obtain

$$\begin{aligned} 2(\mathbf{w}^\top \mathbf{B} \mathbf{w}) \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} - (\mathbf{w}^\top \mathbf{w})^2 \\ = \left[\sum_{i=1}^k \alpha_i v_i + \sum_{i=2k+1}^m \lambda_i u_i^2 \right] \left[\sum_{i=1}^k \frac{2(1/\alpha_i)}{1 + (\beta_i/\alpha_i)^2} v_i + \sum_{i=2k+1}^m \frac{2}{\lambda_i} u_i^2 \right] - \left(\sum_{i=1}^m u_i^2 \right)^2. \end{aligned}$$

From the assumption, we can take a positive number ε (< 1) such that the inequalities $|\beta_i/\alpha_i| \leq 1 - \varepsilon$ hold for $1 \leq i \leq k$. The substitution of σ_i into the above identity imply

$$\begin{aligned} 2(\mathbf{w}^\top \mathbf{B} \mathbf{w}) \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} - (\mathbf{w}^\top \mathbf{w})^2 \\ \geq \left[\sum_{i=1}^k \alpha_i v_i + \sum_{i=2k+1}^m \lambda_i u_i^2 \right] \left[\sum_{i=1}^k \frac{2}{1 + (1-\varepsilon)^2} \left(\frac{1}{\alpha_i} \right) v_i + \sum_{i=2k+1}^m \frac{2}{\lambda_i} u_i^2 \right] - \left(\sum_{i=1}^m u_i^2 \right)^2 \\ = \left(\sum_{i=1}^m \sigma_i u_i^2 \right) \left(\sum_{i=1}^m \frac{1}{\sigma_i} u_i^2 \right) - \left(\sum_{i=1}^m u_i^2 \right)^2 + R_2 \\ = \sum_{i=1}^m u_i^4 + \sum_{i>j}^m \frac{\sigma_i^2 + \sigma_j^2}{\sigma_i \sigma_j} u_i^2 u_j^2 - \sum_{i=1}^m u_i^4 - 2 \sum_{i>j}^m u_i^2 u_j^2 + R_2 \\ = \sum_{i>j}^m \frac{(\sigma_i - \sigma_j)^2}{\sigma_i \sigma_j} u_i^2 u_j^2 + R_2 \\ = R_1 + R_2, \end{aligned}$$

where

$$R_1 = \sum_{i>j}^m \frac{(\sigma_i - \sigma_j)^2}{\sigma_i \sigma_j} u_i^2 u_j^2,$$

$$R_2 = \left(\sum_{i=1}^m \sigma_i u_i^2 \right) \left[\sum_{i=1}^k \frac{2\varepsilon - \varepsilon^2}{1 + (1 - \varepsilon)^2} \left(\frac{1}{\alpha_i} \right) v_i + \sum_{i=2k+1}^m \frac{1}{\lambda_i} u_i^2 \right].$$

Thus, if we take δ so as $0 < \delta \leq \varepsilon < 1$, the above inequality brings the estimation

$$\begin{aligned} & (2 - \delta) (\mathbf{w}^\top \mathbf{B} \mathbf{w}) \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} - (\mathbf{w}^\top \mathbf{w})^2 \\ & \geq R_1 + \left(\sum_{i=1}^m \sigma_i u_i^2 \right) \left[\sum_{i=1}^k \frac{2\varepsilon - \varepsilon^2 - \delta [1 + (1 - \varepsilon)^2]}{1 + (1 - \varepsilon)^2} \left(\frac{1}{\alpha_i} \right) v_i + \sum_{i=2k+1}^m \frac{1 - \delta}{\lambda_i} u_i^2 \right] \\ & = R_1 + \left(\sum_{i=1}^m \sigma_i u_i^2 \right) \left[\sum_{i=1}^k \frac{(2 - \varepsilon)(\varepsilon - \delta) + \delta \varepsilon (1 - \varepsilon)}{1 + (1 - \varepsilon)^2} \left(\frac{1}{\alpha_i} \right) v_i + \sum_{i=2k+1}^m \frac{1 - \delta}{\lambda_i} u_i^2 \right] > 0. \end{aligned}$$

Hence we obtain

$$(2 - \delta) (\mathbf{w}^\top \mathbf{B} \mathbf{w}) \frac{1}{2} \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} > (\mathbf{w}^\top \mathbf{w})^2,$$

and the desired result (4) follows from the negative definiteness of \mathbf{B} and $(\mathbf{B}^{-1} + \mathbf{B}^{-\top})$.

Conversely, suppose that for some i the inequality $|\beta_i/\alpha_i| \geq 1$ holds. Considering a vector \mathbf{u} having nonzero entries only u_{2i-1} and u_{2i} , it suffices to evaluate the case of $m = 2$ with

$$\mathbf{B} = \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \end{bmatrix}$$

and $|\beta/\alpha| \geq 1$. Then, we have

$$\begin{aligned} (\mathbf{w}^\top \mathbf{w})^2 &= (w_1^2 + w_2^2)^2, \\ \mathbf{w}^\top \mathbf{B} \mathbf{w} &= \alpha (w_1^2 + w_2^2), \\ \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w} &= \frac{2\alpha}{\alpha^2 + \beta^2} (w_1^2 + w_2^2). \end{aligned}$$

Hence, these identities and the assumption that $|\beta/\alpha| \geq 1$ lead to

$$\frac{(\mathbf{w}^\top \mathbf{w})^2}{(\mathbf{w}^\top \mathbf{B} \mathbf{w}) \cdot (1/2) \mathbf{w}^\top (\mathbf{B}^{-1} + \mathbf{B}^{-\top}) \mathbf{w}} = 1 + \left(\frac{\beta}{\alpha} \right)^2 \geq 2. \quad \blacksquare$$

3. A STABILITY RESULT

Applying Lemma 2, we arrive at our main result.

THEOREM 2. *The numerical solution by Lambert's method of the problem with a normal matrix satisfying Assumption A converges to 0 monotonically in L_2 -norm if the eigenvalues of the matrix fulfill the condition $|\beta_i/\alpha_i| < 1$ for $1 \leq i \leq k$.*

PROOF. Let l and L be the same quantities as in Lemma 2. From (3), we obtain the estimation

$$l \leq \frac{\mathbf{f}_n^\top \mathbf{A} \mathbf{f}_n}{\mathbf{f}_n^\top \mathbf{f}_n} \leq L,$$

which implies

$$-\frac{1}{l} \leq h_n^* \leq -\frac{1}{L}. \quad (9)$$

Applying Lambert's method (2) to the given problem yields

$$\mathbf{y}_{n+1} = (\mathbf{I} + h_n \mathbf{A}) \mathbf{y}_n.$$

Therefore,

$$\begin{aligned} \mathbf{y}_{n+1}^\top \mathbf{y}_{n+1} &= \mathbf{y}_n^\top (\mathbf{I} + h_n \mathbf{A})^\top (\mathbf{I} + h_n \mathbf{A}) \mathbf{y}_n \\ &= \mathbf{y}_n^\top \mathbf{y}_n + h_n \mathbf{y}_n^\top (\mathbf{A}^\top + \mathbf{A}) \mathbf{y}_n + h_n^2 \mathbf{y}_n^\top \mathbf{A}^\top \mathbf{A} \mathbf{y}_n. \end{aligned}$$

Hence, the equation

$$\frac{\|\mathbf{y}_{n+1}\|_2^2}{\|\mathbf{y}_n\|_2^2} = 1 - T_n \quad (10)$$

holds, where

$$T_n = -\frac{(1/2)h_n \mathbf{y}_n^\top (\mathbf{A}^\top + \mathbf{A}) \mathbf{y}_n}{\mathbf{y}_n^\top \mathbf{y}_n} \left(2 + \frac{h_n \mathbf{y}_n^\top \mathbf{A}^\top \mathbf{A} \mathbf{y}_n}{(1/2) \mathbf{y}_n^\top (\mathbf{A}^\top + \mathbf{A}) \mathbf{y}_n} \right).$$

Since $\mathbf{f}_n = \mathbf{A} \mathbf{y}_n$, we have

$$T_n = \frac{-(1/2)h_n \mathbf{y}_n^\top (\mathbf{A}^\top + \mathbf{A}) \mathbf{y}_n}{\mathbf{y}_n^\top \mathbf{y}_n} \left(2 + \frac{h_n \mathbf{f}_n^\top \mathbf{f}_n}{(1/2) \mathbf{f}_n^\top (\mathbf{A}^{-1} + \mathbf{A}^{-\top}) \mathbf{f}_n} \right). \quad (11)$$

The definition of h_n implies

$$h_n \leq h_n^* = -\frac{\mathbf{f}_n^\top \mathbf{f}_n}{\mathbf{f}_n^\top \mathbf{A} \mathbf{f}_n},$$

which, along with the negativeness of $\mathbf{f}_n^\top (\mathbf{A}^{-1} + \mathbf{A}^{-\top}) \mathbf{f}_n$ and (4), yields

$$\begin{aligned} \frac{h_n \mathbf{f}_n^\top \mathbf{f}_n}{(1/2) \mathbf{f}_n^\top (\mathbf{A}^{-1} + \mathbf{A}^{-\top}) \mathbf{f}_n} &\geq \frac{h_n^* \mathbf{f}_n^\top \mathbf{f}_n}{(1/2) \mathbf{f}_n^\top (\mathbf{A}^{-1} + \mathbf{A}^{-\top}) \mathbf{f}_n} \\ &= \frac{-(\mathbf{f}_n^\top \mathbf{f}_n)^2}{(\mathbf{f}_n^\top \mathbf{A} \mathbf{f}_n) \cdot (1/2) \mathbf{f}_n^\top (\mathbf{A}^{-1} + \mathbf{A}^{-\top}) \mathbf{f}_n} > -2 + \delta. \end{aligned}$$

From equation (11), we thus have the bound

$$T_n > -\frac{(1/2)h_n \mathbf{y}_n^\top (\mathbf{A}^\top + \mathbf{A}) \mathbf{y}_n}{\mathbf{y}_n^\top \mathbf{y}_n} \delta,$$

and, together with (3), we furthermore obtain

$$T_n > -\delta h_n L.$$

CASE 1. $h_0 < h_n^*$. Then $h_n = h_0$ and $T_n > -\delta h_0 L =: \gamma_1 > 0$. (Note that $\gamma_1 < -\delta h_n^* L \leq \delta < 1$ by the inequality (9).)

CASE 2. $h_0 \geq h_n^*$. Then $h_n = h_n^*$ and $T_n > -\delta h_n^* L \geq \delta L/l =: \gamma_2 > 0$ by the inequality (9). (Again note that $\gamma_2 < 1$.)

If we take $\gamma = \min(\gamma_1, \gamma_2)$, then $T_n > \gamma > 0$ holds for all n , and the result is established. \blacksquare

This theorem indicates that Lambert's method is acceptable for a linear system with real normal matrix coefficients if all of its eigenvalues lie in the sector of the angle within $\pm 45^\circ$ from negative real axis. We note that, in the case where the initial steplength, h_0 , is smaller than the amount which is determined by the stability condition for Euler's rule, Lambert's method (2) is always stable regardless of the size of $|\beta_i/\alpha_i|$ because h_n is always chosen to be smaller than that amount.

4. NUMERICAL EXPERIMENTS

We will confirm Theorem 2 through a numerical example. We consider the following constant coefficient linear problem whose Jacobian matrix is real and normal.

$$\begin{aligned} \begin{bmatrix} y_1'(x) \\ y_2'(x) \end{bmatrix} &= \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \end{bmatrix} \begin{bmatrix} y_1(x) \\ y_2(x) \end{bmatrix} \quad \text{for } 0 \leq x \leq 10, \\ \begin{bmatrix} y_1(0) \\ y_2(0) \end{bmatrix} &= \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \end{aligned}$$

where α and β are real constants. The eigenvalues of this problem are $\alpha \pm i\beta$, and the theoretical solution is

$$\begin{bmatrix} y_1(x) \\ y_2(x) \end{bmatrix} = \begin{bmatrix} [\cos(\beta x) + \sin(\beta x)] \exp(\alpha x) \\ [\cos(\beta x) - \sin(\beta x)] \exp(\alpha x) \end{bmatrix}.$$

We applied the method (2) to this IVP with $\alpha = -10$ and $\beta = 8, 10, 12$. Numerical calculations are summarized in Table 1, where “Euler’s Condition” means the maximum allowable steplength when Euler’s rule is applied to this IVP. Error in Table 1 is the maximum of absolute error at the endpoint, $t = 10$. (The numerical solutions at $t = 10$ were computed by a linear interpolant over the last step.)

Table 1. Numerical results.

Eigenvalues	Euler’s Condition	h_0	Error
$-10 \pm 8i$	0.12	0.1	2.04×10^{-10}
		0.2	2.04×10^{-10}
$-10 \pm 10i$	0.10	0.08	4.81×10^{-11}
		0.12	1.00
$-10 \pm 12i$	0.082	0.07	1.00×10^{-7}
		0.09	1.05×10^4

From Table 1, we can observe that Lambert’s method gives stable solutions for every initial steplength h_0 if the conditions of Theorem 2 are satisfied. But the numerical solution loses its stability if the conditions of Theorem 2 are violated and the initial steplength is larger than the “Euler’s Condition.” This fact endorses our Theorem 2. We note that when $\alpha = \beta$ and h_0 is larger than the “Euler’s Condition,” equation (10) indicates that the magnitude of the numerical solution does not change since, in this case, $T_n = 0$ (if $h_n^* \leq h_0$). This is verified by the numerical result with $\beta = 10$ and $h_0 = 0.12$.

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